autogluon_each_location

October 6, 2023

[1]:
```
import pandas as pd
from darts import TimeSeries
import numpy as np



import warnings
warnings.filterwarnings("ignore")

def fix_datetime(X, name):
    """
    Function to fix and standardize datetime in the given DataFrame.

    Parameters:
    - X: DataFrame to be modified.
    - name: String representing the name of the DataFrame, used for logging.

    Returns:
    - Modified DataFrame with standardized datetime.
    """

    # Convert 'date_forecast' to datetime format and replace original column␣
 ↪with 'ds'
    X['ds'] = pd.to_datetime(X['date_forecast'])
    X.drop(columns=['date_forecast'], inplace=True, errors='ignore')

    # Sort DataFrame by the new datetime column ('ds') and set it as the index
    X.sort_values(by='ds', inplace=True)
    X.set_index('ds', inplace=True)

    # Log the shape of the DataFrame before dropping rows with in-between␣
 ↪minutes
    print(f"Shape of {name} before dropping in-between hour rows: ", X.shape)

    # Identify and log gaps in the date sequence
    print(f"HEIHEI: {name} gaps in dates: ", X.index.to_series().diff().dt.
 ↪total_seconds().gt(60*15).sum())
```

```python
    print(f"HEIHEI: {name} first gap in dates: ", X[X.index.to_series().diff().
↪dt.total_seconds().gt(60*15)==True].index[:1])

    # Calculate and log the size of each gap in the date sequence
    temp = X.index.to_series().diff().dt.total_seconds()
    if temp.shape[0] > 0:
        print(f"HEIHEI: {name} list of size (in days) of each gap: ", temp[temp.
↪gt(60*15)].values / (60*60*24))

    # temporarily transform into darts time series to fill missing dates
    # get date_calc if date_calc is column in X
    temp_calc = None
    if "date_calc" in X.columns:
        temp_calc = X["date_calc"]
        X.drop(columns=['date_calc'], inplace=True)
    X = TimeSeries.from_dataframe(df=X, freq="15T", fill_missing_dates=True,␣
↪fillna_value=None).pd_dataframe()
    if temp_calc is not None:
        X["date_calc"] = temp_calc

    print(f"HEIHEI: {name} gaps in dates after filling missing dates: ", X.
↪index.to_series().diff().dt.total_seconds().gt(60*15).sum())


    # Drop rows where the minute part of the time is not 0
    X = X[X.index.minute == 0]

    # Log the shape of the DataFrame after dropping rows with in-between minutes
    print(f"Shape of {name} after dropping in-between hour rows: ", X.shape)

    return X



def convert_to_datetime(X_train_observed, X_train_estimated, X_test, y_train):
    X_train_observed = fix_datetime(X_train_observed, "X_train_observed")
    X_train_estimated = fix_datetime(X_train_estimated, "X_train_estimated")
    X_test = fix_datetime(X_test, "X_test")


    X_train_observed["estimated_diff_hours"] = 0
    X_train_estimated["estimated_diff_hours"] = (X_train_estimated.index - pd.
↪to_datetime(X_train_estimated["date_calc"])).dt.total_seconds() / 3600
    X_test["estimated_diff_hours"] = (X_test.index - pd.
↪to_datetime(X_test["date_calc"])).dt.total_seconds() / 3600
```

```python
    X_train_estimated.drop(columns=['date_calc'], inplace=True)
    X_test.drop(columns=['date_calc'], inplace=True)

    y_train['ds'] = pd.to_datetime(y_train['time'])
    y_train.drop(columns=['time'], inplace=True)
    y_train.sort_values(by='ds', inplace=True)
    y_train.set_index('ds', inplace=True)

    return X_train_observed, X_train_estimated, X_test, y_train




# location_map = {
#     "A": 0,
#     "B": 1,
#     "C": 2
# }


def preprocess_data(X_train_observed, X_train_estimated, X_test, y_train, location):
    # convert to datetime
    X_train_observed, X_train_estimated, X_test, y_train = convert_to_datetime(X_train_observed, X_train_estimated, X_test, y_train)


    # # cast all columns to float64
    # X_train = X_train.astype('float64')
    # X_test = X_test.astype('float64')


    print(f"X_train_observed shape: {X_train_observed.shape}")
    print(f"X_train_estimated shape: {X_train_estimated.shape}")
    print(f"X_test shape: {X_test.shape}")
    print(f"y_train shape: {y_train.shape}")



    y_train["y"] = y_train["pv_measurement"].astype('float64')
    y_train.drop(columns=['pv_measurement'], inplace=True)
    print("y_train columns: ", y_train.columns)

    # temporarily transform into darts time series to fill missing dates
    print("Shape of y_train before filling missing dates: ", y_train.shape)
    y_train = TimeSeries.from_dataframe(df=y_train, freq="H", fill_missing_dates=True, fillna_value=None).pd_dataframe()
```

```python
    print("Shape of y_train after filling missing dates: ", y_train.shape)


    # number of gaps in X_train_observed + X_train_estimated before
    print(f"LOOK: Number of gaps in X_train_observed plus number of gaps in X_train_estimated before: ", X_train_observed.index.to_series().diff().dt.total_seconds().gt(3600).sum() + X_train_estimated.index.to_series().diff().dt.total_seconds().gt(3600).sum())
    X_train = pd.concat([X_train_observed, X_train_estimated])
    print(f"LOOK: Number of gaps in X_train_observed plus number of gaps in X_train_estimated after: ", X_train.index.to_series().diff().dt.total_seconds().gt(3600).sum())
    # print size of gaps in X_train
    temp = X_train.index.to_series().diff().dt.total_seconds()
    if temp.shape[0] > 0:
        print("LOOK: list of size (in days) of each gap: ", temp[temp.gt(3600)].values / (60*60*24))
    print("if the number is bigger after than before that means there is a gap in time between the observed and estimated training sets")

    # print info on dates in X_train, and if there are any missing dates
    print("X_train dates info: ", X_train.index.min(), X_train.index.max(), X_train.index.max() - X_train.index.min())
    print("X_test dates info: ", X_test.index.min(), X_test.index.max(), X_test.index.max() - X_test.index.min())
    print("y_train dates info: ", y_train.index.min(), y_train.index.max(), y_train.index.max() - y_train.index.min())

    # any gaps in dates?
    print("X_train gaps in dates: ", X_train.index.to_series().diff().dt.total_seconds().gt(3600).sum())
    print("X_test gaps in dates: ", X_test.index.to_series().diff().dt.total_seconds().gt(3600).sum())
    print("y_train gaps in dates: ", y_train.index.to_series().diff().dt.total_seconds().gt(3600).sum())

    # temporarily transform into darts time series to fill missing dates
    X_train = TimeSeries.from_dataframe(df=X_train, freq="H", fill_missing_dates=True, fillna_value=None).pd_dataframe()
    X_test = TimeSeries.from_dataframe(df=X_test, freq="H", fill_missing_dates=True, fillna_value=None).pd_dataframe()
    print("X_train gaps in dates after filling missing dates: ", X_train.index.to_series().diff().dt.total_seconds().gt(3600).sum())
    print("X_test gaps in dates after filling missing dates: ", X_test.index.to_series().diff().dt.total_seconds().gt(3600).sum())
```

```python
    # clip all y values to 0 if negative
    y_train["y"] = y_train["y"].clip(lower=0)

    # print Number of missing values in X train
    print("Number of missing values in X_train: ", X_train.isnull().sum().sum())
    print("Number of missing values in X_test: ", X_test.isnull().sum().sum())
    # y_train missing values
    print("Number of missing values in y_train: ", y_train.isnull().sum().sum())
    X_train = pd.merge(X_train, y_train, how="outer", left_index=True,␣
↪right_index=True)
    print("Number of missing values in X_train after merging with y_train: ",␣
↪X_train.drop(columns=['y']).isnull().sum().sum())



    X_train["location"] = location
    X_test["location"] = location

    return X_train, X_test



# Define locations
locations = ['A', 'B', 'C']

X_trains = []
X_tests = []
y_trains = []
# Loop through locations
for loc in locations:
    print("\n\n")
    print(f"Processing location {loc}...")
    # Read target training data
    y_train = pd.read_parquet(f'{loc}/train_targets.parquet')

    # Read estimated training data and add location feature
    X_train_estimated = pd.read_parquet(f'{loc}/X_train_estimated.parquet')

    # Read observed training data and add location feature
    X_train_observed= pd.read_parquet(f'{loc}/X_train_observed.parquet')

    # Read estimated test data and add location feature
    X_test_estimated = pd.read_parquet(f'{loc}/X_test_estimated.parquet')

    # Concatenate observed and estimated datasets for each location
```

```
    #X_train = pd.concat([X_train_estimated, X_train_observed])




    # Preprocess data
    X_train, X_test = preprocess_data(X_train_observed, X_train_estimated, X_test_estimated, y_train, loc)

    print(f"Final shape of X_train for location {loc}: ", X_train.shape)
    print(f"Final shape of X_test for location {loc}: ", X_test.shape)

    # print(y_train.head(), y_train.shape)
    # print(X_train.head(), X_train.shape)
    # print(X_train.head(), X_train.shape)
    # print(type(X_train['y']))

    # Save data to csv
    X_train.to_csv(f'{loc}/X_train.csv', index=True)
    X_test.to_csv(f'{loc}/X_test.csv', index=True)


    X_trains.append(X_train)
    X_tests.append(X_test)

# Concatenate all data and save to csv
X_train = pd.concat(X_trains)
X_test = pd.concat(X_tests)

print(f"Final shape of X_train: ", X_train.shape)
print(f"Final shape of X_test: ", X_test.shape)

# temporary
#X_train["hour"] = X_train.index.hour
#X_train["day"] = X_train.index.day
#X_train["month"] = X_train.index.month
#X_train["dayofweek"] = X_train.index.dayofweek
#X_train["year"] = X_train.index.year
#X_train["ds2"] = X_train.index.astype("int64")


#X_test["hour"] = X_test.index.hour
#X_test["day"] = X_test.index.day
#X_test["month"] = X_test.index.month
#X_test["dayofweek"] = X_test.index.dayofweek
#X_test["year"] = X_test.index.year
#X_test["ds2"] = X_test.index.astype("int64")
```

```python
X_train.dropna(subset=['y'], inplace=True)
X_train.to_csv('X_train_raw.csv', index=True)
X_test.to_csv('X_test_raw.csv', index=True)
```

```
Processing location A…
Shape of X_train_observed before dropping in-between hour rows:  (118669, 45)
HEIHEI: X_train_observed gaps in dates:  0
HEIHEI: X_train_observed first gap in dates:  DatetimeIndex([],
dtype='datetime64[ns]', name='ds', freq=None)
HEIHEI: X_train_observed list of size (in days) of each gap:  []
HEIHEI: X_train_observed gaps in dates after filling missing dates:  0
Shape of X_train_observed after dropping in-between hour rows:  (29668, 45)
Shape of X_train_estimated before dropping in-between hour rows:  (17576, 46)
HEIHEI: X_train_estimated gaps in dates:  1
HEIHEI: X_train_estimated first gap in dates:  DatetimeIndex(['2023-01-27'],
dtype='datetime64[ns]', name='ds', freq=None)
HEIHEI: X_train_estimated list of size (in days) of each gap:  [1.01041667]
HEIHEI: X_train_estimated gaps in dates after filling missing dates:  0
Shape of X_train_estimated after dropping in-between hour rows:  (4418, 46)
Shape of X_test before dropping in-between hour rows:  (2880, 46)
HEIHEI: X_test gaps in dates:  17
HEIHEI: X_test first gap in dates:  DatetimeIndex(['2023-05-06'],
dtype='datetime64[ns]', name='ds', freq=None)
HEIHEI: X_test list of size (in days) of each gap:  [4.01041667 7.01041667
3.01041667 1.01041667 1.01041667 1.01041667
 1.01041667 1.01041667 1.01041667 2.01041667 1.01041667 1.01041667
 3.01041667 2.01041667 3.01041667 1.01041667 1.01041667]
HEIHEI: X_test gaps in dates after filling missing dates:  0
Shape of X_test after dropping in-between hour rows:  (1536, 46)
X_train_observed shape: (29668, 46)
X_train_estimated shape: (4418, 46)
X_test shape: (1536, 46)
y_train shape: (34085, 1)
y_train columns:  Index(['y'], dtype='object')
Shape of y_train before filling missing dates:  (34085, 1)
Shape of y_train after filling missing dates:  (34274, 1)
LOOK: Number of gaps in X_train_observed plus number of gaps in
X_train_estimated before:  0
LOOK: Number of gaps in X_train_observed plus number of gaps in
X_train_estimated after:  1
LOOK: list of size (in days) of each gap:  [7.875]
if the number is bigger after than before that means there is a gap in time
between the observed and estimated training sets
```

```
X_train dates info:  2019-06-02 22:00:00 2023-04-30 23:00:00 1428 days 01:00:00
X_test dates info:  2023-05-01 00:00:00 2023-07-03 23:00:00 63 days 23:00:00
y_train dates info:  2019-06-02 22:00:00 2023-04-30 23:00:00 1428 days 01:00:00
X_train gaps in dates:  1
X_test gaps in dates:  0
y_train gaps in dates:  0
X_train gaps in dates after filling missing dates:  0
X_test gaps in dates after filling missing dates:  0
Number of missing values in X_train:  53521
Number of missing values in X_test:  38573
Number of missing values in y_train:  189
Number of missing values in X_train after merging with y_train:  53521
Final shape of X_train for location A:  (34274, 48)
Final shape of X_test for location A:  (1536, 47)


Processing location B…
Shape of X_train_observed before dropping in-between hour rows:  (116929, 45)
HEIHEI: X_train_observed gaps in dates:  0
HEIHEI: X_train_observed first gap in dates:  DatetimeIndex([],
dtype='datetime64[ns]', name='ds', freq=None)
HEIHEI: X_train_observed list of size (in days) of each gap:  []
HEIHEI: X_train_observed gaps in dates after filling missing dates:  0
Shape of X_train_observed after dropping in-between hour rows:  (29233, 45)
Shape of X_train_estimated before dropping in-between hour rows:  (17576, 46)
HEIHEI: X_train_estimated gaps in dates:  1
HEIHEI: X_train_estimated first gap in dates:  DatetimeIndex(['2023-01-27'],
dtype='datetime64[ns]', name='ds', freq=None)
HEIHEI: X_train_estimated list of size (in days) of each gap:  [1.01041667]
HEIHEI: X_train_estimated gaps in dates after filling missing dates:  0
Shape of X_train_estimated after dropping in-between hour rows:  (4418, 46)
Shape of X_test before dropping in-between hour rows:  (2880, 46)
HEIHEI: X_test gaps in dates:  17
HEIHEI: X_test first gap in dates:  DatetimeIndex(['2023-05-06'],
dtype='datetime64[ns]', name='ds', freq=None)
HEIHEI: X_test list of size (in days) of each gap:  [4.01041667 7.01041667
3.01041667 1.01041667 1.01041667 1.01041667
 1.01041667 1.01041667 1.01041667 2.01041667 1.01041667 1.01041667
 3.01041667 2.01041667 3.01041667 1.01041667 1.01041667]
HEIHEI: X_test gaps in dates after filling missing dates:  0
Shape of X_test after dropping in-between hour rows:  (1536, 46)
X_train_observed shape: (29233, 46)
X_train_estimated shape: (4418, 46)
X_test shape: (1536, 46)
y_train shape: (32848, 1)
y_train columns:  Index(['y'], dtype='object')
Shape of y_train before filling missing dates:  (32848, 1)
```

```
Shape of y_train after filling missing dates:  (37945, 1)
LOOK: Number of gaps in X_train_observed plus number of gaps in
X_train_estimated before:  0
LOOK: Number of gaps in X_train_observed plus number of gaps in
X_train_estimated after:  1
LOOK: list of size (in days) of each gap:  [178.91666667]
if the number is bigger after than before that means there is a gap in time
between the observed and estimated training sets
X_train dates info:  2019-01-01 00:00:00 2023-04-30 23:00:00 1580 days 23:00:00
X_test dates info:  2023-05-01 00:00:00 2023-07-03 23:00:00 63 days 23:00:00
y_train dates info:  2018-12-31 23:00:00 2023-04-30 23:00:00 1581 days 00:00:00
X_train gaps in dates:  1
X_test gaps in dates:  0
y_train gaps in dates:  0
X_train gaps in dates after filling missing dates:  0
X_test gaps in dates after filling missing dates:  0
Number of missing values in X_train:  239726
Number of missing values in X_test:  38553
Number of missing values in y_train:  5101
Number of missing values in X_train after merging with y_train:  239772
Final shape of X_train for location B:  (37945, 48)
Final shape of X_test for location B:  (1536, 47)



Processing location C…
Shape of X_train_observed before dropping in-between hour rows:  (116825, 45)
HEIHEI: X_train_observed gaps in dates:  0
HEIHEI: X_train_observed first gap in dates:  DatetimeIndex([],
dtype='datetime64[ns]', name='ds', freq=None)
HEIHEI: X_train_observed list of size (in days) of each gap:  []
HEIHEI: X_train_observed gaps in dates after filling missing dates:  0
Shape of X_train_observed after dropping in-between hour rows:  (29207, 45)
Shape of X_train_estimated before dropping in-between hour rows:  (17576, 46)
HEIHEI: X_train_estimated gaps in dates:  1
HEIHEI: X_train_estimated first gap in dates:  DatetimeIndex(['2023-01-27'],
dtype='datetime64[ns]', name='ds', freq=None)
HEIHEI: X_train_estimated list of size (in days) of each gap:  [1.01041667]
HEIHEI: X_train_estimated gaps in dates after filling missing dates:  0
Shape of X_train_estimated after dropping in-between hour rows:  (4418, 46)
Shape of X_test before dropping in-between hour rows:  (2880, 46)
HEIHEI: X_test gaps in dates:  17
HEIHEI: X_test first gap in dates:  DatetimeIndex(['2023-05-06'],
dtype='datetime64[ns]', name='ds', freq=None)
HEIHEI: X_test list of size (in days) of each gap:  [4.01041667 7.01041667
3.01041667 1.01041667 1.01041667 1.01041667
 1.01041667 1.01041667 1.01041667 2.01041667 1.01041667 1.01041667
 3.01041667 2.01041667 3.01041667 1.01041667 1.01041667]
```

```
HEIHEI: X_test gaps in dates after filling missing dates:  0
Shape of X_test after dropping in-between hour rows:  (1536, 46)
X_train_observed shape: (29207, 46)
X_train_estimated shape: (4418, 46)
X_test shape: (1536, 46)
y_train shape: (32155, 1)
y_train columns:  Index(['y'], dtype='object')
Shape of y_train before filling missing dates:  (32155, 1)
Shape of y_train after filling missing dates:  (37945, 1)
LOOK: Number of gaps in X_train_observed plus number of gaps in
X_train_estimated before:  0
LOOK: Number of gaps in X_train_observed plus number of gaps in
X_train_estimated after:  1
LOOK: list of size (in days) of each gap:  [180.]
if the number is bigger after than before that means there is a gap in time
between the observed and estimated training sets
X_train dates info:  2019-01-01 00:00:00 2023-04-30 23:00:00 1580 days 23:00:00
X_test dates info:  2023-05-01 00:00:00 2023-07-03 23:00:00 63 days 23:00:00
y_train dates info:  2018-12-31 23:00:00 2023-04-30 23:00:00 1581 days 00:00:00
X_train gaps in dates:  1
X_test gaps in dates:  0
y_train gaps in dates:  0
X_train gaps in dates after filling missing dates:  0
X_test gaps in dates after filling missing dates:  0
Number of missing values in X_train:  240647
Number of missing values in X_test:  38610
Number of missing values in y_train:  11850
Number of missing values in X_train after merging with y_train:  240693
Final shape of X_train for location C:  (37945, 48)
Final shape of X_test for location C:  (1536, 47)
Final shape of X_train:  (110164, 48)
Final shape of X_test:  (4608, 47)
```

[2]:
```python
import pandas as pd

df = X_train.copy()
test_df = X_test.copy()



# add sin and cos of sun_elevation:d and sun_azimuth:d
df['sin_sun_elevation'] = np.sin(np.deg2rad(df['sun_elevation:d']))

test_df['sin_sun_elevation'] = np.sin(np.deg2rad(test_df['sun_elevation:d']))

# add global_rad_1h:J = diffuse_rad_1h:J + direct_rad_1h:J
df['global_rad_1h:J'] = df['diffuse_rad_1h:J'] + df['direct_rad_1h:J']
```

```python
test_df['global_rad_1h:J'] = test_df['diffuse_rad_1h:J'] +␣
↪test_df['direct_rad_1h:J']

# dew_or_rime:idx, Change this to one variable for is_dew and one variable for␣
↪is_rime (dew:1, rime:-1)
df['is_dew'] = df['dew_or_rime:idx'].apply(lambda x: 1 if x == 1 else 0)
df['is_rime'] = df['dew_or_rime:idx'].apply(lambda x: 1 if x == -1 else 0)

test_df['is_dew'] = test_df['dew_or_rime:idx'].apply(lambda x: 1 if x == 1 else␣
↪0)
test_df['is_rime'] = test_df['dew_or_rime:idx'].apply(lambda x: 1 if x == -1␣
↪else 0)


EXOGENOUS = [
    'estimated_diff_hours',
    "absolute_humidity_2m:gm3",
    "air_density_2m:kgm3",
    "dew_point_2m:K",
    "diffuse_rad_1h:J",
    "direct_rad_1h:J",
    "effective_cloud_cover:p",
    "fresh_snow_1h:cm",
    "snow_depth:cm",
    "sun_elevation:d",
    "sun_azimuth:d",
    "t_1000hPa:K",
    "visibility:m",
    "wind_speed_10m:ms",
    "is_dew",
    "is_rime",
    "sin_sun_elevation",
    "global_rad_1h:J",
    ]
#additional_features_for_testing =

df = df[EXOGENOUS + ["y", "location"]]
test_df = test_df[EXOGENOUS+ ["location"]]

# save to X_train_feature_engineered.csv
df.to_csv('X_train_feature_engineered.csv', index=True)
test_df.to_csv('X_test_feature_engineered.csv', index=True)
```

1 Starting

[3]:
```
import os
# Get the last submission number
last_submission_number = int(max([int(filename.split('_')[1].split('.')[0]) for␣
↪filename in os.listdir('submissions') if "submission" in filename]))
print("Last submission number:", last_submission_number)
print("Now creating submission number:", last_submission_number + 1)

# Create the new filename
new_filename = f'submission_{last_submission_number + 1}'
```

```
Last submission number: 76
Now creating submission number: 77
```

[4]:
```
from autogluon.tabular import TabularDataset, TabularPredictor
train_data = TabularDataset('X_train_raw.csv')
train_data.drop(columns=['ds'], inplace=True)

label = 'y'
metric = 'mean_absolute_error'
time_limit = 60*1
presets = 'best_quality'
```

[5]:
```
predictors = [None, None, None]
```

[6]:
```
loc = "A"
print(f"Training model for location {loc}...")
predictor = TabularPredictor(label=label, eval_metric=metric,␣
↪path=f"AutogluonModels/{new_filename}_{loc}").
↪fit(train_data[train_data["location"] == loc], time_limit=time_limit,␣
↪presets=presets)
predictors[0] = predictor
```

```
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 60s
AutoGluon will save models to "AutogluonModels/submission_77_A/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.191-1 (2023-08-16)
Disk Space Avail:   53.85 GB / 105.09 GB (51.2%)
Train Data Rows:    34085
Train Data Columns: 47
Label Column: y
```

```
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (5733.42, 0.0, 630.59471,
1165.90242)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    132294.88 MB
        Train Data (Original)  Memory Usage: 14.52 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 3 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…

Training model for location A…

        Useless Original Features (Count: 1): ['location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Unused Original Features (Count: 1): ['snow_drift:idx']
                These features were not used to generate any of the output
features. Add a feature generator compatible with these features to utilize
them.
                Features can also be unused if they carry very little
information, such as being categorical but having almost entirely unique values
or being duplicates of other features.
                These features do not need to be present at inference time.
                ('float', []) : 1 | ['snow_drift:idx']
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 45 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
        Types of features in processed data (raw dtype, special dtypes):
```

```
                ('float', [])     : 43 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', ['bool']) :  2 | ['elevation:m', 'snow_density:kgm3']
        0.5s = Fit runtime
        45 features in original data used to generate 45 features in processed
data.
        Train Data (Processed) Memory Usage: 11.79 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.51s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
AutoGluon will fit 2 stack levels (L1 to L2) …
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 39.65s of the
59.48s of remaining time.
        -299.7196        = Validation score   (-mean_absolute_error)
        0.04s    = Training   runtime
        0.4s     = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 39.12s of the
58.95s of remaining time.
        -300.7579        = Validation score   (-mean_absolute_error)
        0.04s    = Training   runtime
        0.41s    = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 38.61s of the
```

```
58.45s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -171.6107        = Validation score   (-mean_absolute_error)
        28.27s   = Training   runtime
        20.69s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 0.8s of the 20.64s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -206.5569        = Validation score   (-mean_absolute_error)
        0.83s    = Training   runtime
        0.06s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 59.49s of the
18.74s of remaining time.
        -171.2413        = Validation score   (-mean_absolute_error)
        0.38s    = Training   runtime
        0.0s     = Validation runtime
Fitting 9 L2 models …
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 18.35s of the
18.33s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -173.0582        = Validation score   (-mean_absolute_error)
        2.79s    = Training   runtime
        0.19s    = Validation runtime
Fitting model: LightGBM_BAG_L2 … Training model for up to 14.47s of the 14.47s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -170.8816        = Validation score   (-mean_absolute_error)
        1.77s    = Training   runtime
        0.1s     = Validation runtime
Fitting model: RandomForestMSE_BAG_L2 … Training model for up to 11.62s of the
11.61s of remaining time.
        -169.9378        = Validation score   (-mean_absolute_error)
        11.69s   = Training   runtime
        1.49s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L3 … Training model for up to 59.49s of the
-2.27s of remaining time.
        -168.8202        = Validation score   (-mean_absolute_error)
        0.31s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 62.62s … Best model:
"WeightedEnsemble_L3"
TabularPredictor saved. To load, use: predictor =
```

```
TabularPredictor.load("AutogluonModels/submission_77_A/")
```

[7]:
```python
loc = "B"
print(f"Training model for location {loc}...")
predictor = TabularPredictor(label=label, eval_metric=metric,␣
  ↪path=f"AutogluonModels/{new_filename}_{loc}").
  ↪fit(train_data[train_data["location"] == loc], time_limit=time_limit,␣
  ↪presets=presets)
predictors[1] = predictor
```

```
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 60s
AutoGluon will save models to "AutogluonModels/submission_77_B/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.191-1 (2023-08-16)
Disk Space Avail:   53.21 GB / 105.09 GB (50.6%)
Train Data Rows:    32844
Train Data Columns: 47
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (1152.3, -0.0, 96.82478, 193.94649)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    131105.87 MB
        Train Data (Original)  Memory Usage: 13.99 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 2 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
```

```
                Fitting DropDuplicatesFeatureGenerator…
Training model for location B…
        Useless Original Features (Count: 1): ['location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 46 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 44 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', ['bool']) :  2 | ['elevation:m', 'snow_density:kgm3']
        0.2s = Fit runtime
        46 features in original data used to generate 46 features in processed
data.
        Train Data (Processed) Memory Usage: 11.63 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.24s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
```

```
}
AutoGluon will fit 2 stack levels (L1 to L2) …
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 39.83s of the
59.76s of remaining time.
        -56.8245         = Validation score   (-mean_absolute_error)
        0.05s    = Training   runtime
        0.39s    = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 39.18s of the
59.1s of remaining time.
        -56.7738         = Validation score   (-mean_absolute_error)
        0.04s    = Training   runtime
        0.39s    = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 38.69s of the
58.62s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -31.2779         = Validation score   (-mean_absolute_error)
        32.17s   = Training   runtime
        21.21s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 1.12s of the 21.04s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -38.8786         = Validation score   (-mean_absolute_error)
        1.69s    = Training   runtime
        0.11s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 59.76s of the
18.06s of remaining time.
        -31.2779         = Validation score   (-mean_absolute_error)
        0.36s    = Training   runtime
        0.0s     = Validation runtime
Fitting 9 L2 models …
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 17.69s of the
17.67s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -29.7487         = Validation score   (-mean_absolute_error)
        5.14s    = Training   runtime
        0.43s    = Validation runtime
Fitting model: LightGBM_BAG_L2 … Training model for up to 11.06s of the 11.05s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -29.3754         = Validation score   (-mean_absolute_error)
        2.25s    = Training   runtime
        0.09s    = Validation runtime
```

```
Fitting model: RandomForestMSE_BAG_L2 … Training model for up to 7.54s of the
7.53s of remaining time.
        -28.2682         = Validation score   (-mean_absolute_error)
        12.63s   = Training   runtime
        1.55s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L3 … Training model for up to 59.76s of the
-7.24s of remaining time.
        -28.2665         = Validation score   (-mean_absolute_error)
        0.31s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 67.58s … Best model:
"WeightedEnsemble_L3"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_77_B/")
```

[8]:

```python
loc = "C"
print(f"Training model for location {loc}...")
predictor = TabularPredictor(label=label, eval_metric=metric,␣
 ↪path=f"AutogluonModels/{new_filename}_{loc}").
 ↪fit(train_data[train_data["location"] == loc], time_limit=time_limit,␣
 ↪presets=presets)
predictors[2] = predictor
```

```
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 60s
AutoGluon will save models to "AutogluonModels/submission_77_C/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.191-1 (2023-08-16)
Disk Space Avail:   52.60 GB / 105.09 GB (50.1%)
Train Data Rows:    26095
Train Data Columns: 47
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and label-values can't be converted to int).
        Label info (max, min, mean, stddev): (999.6, -0.0, 77.63106, 165.81688)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    130946.51 MB
```

```
        Train Data (Original)  Memory Usage: 11.12 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 3 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
```

```
Training model for location C…
```

```
        Useless Original Features (Count: 1): ['location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Unused Original Features (Count: 1): ['snow_drift:idx']
                These features were not used to generate any of the output
features. Add a feature generator compatible with these features to utilize
them.
                Features can also be unused if they carry very little
information, such as being categorical but having almost entirely unique values
or being duplicates of other features.
                These features do not need to be present at inference time.
                ('float', []) : 1 | ['snow_drift:idx']
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 45 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 43 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', ['bool']) :  2 | ['elevation:m', 'snow_density:kgm3']
        0.5s = Fit runtime
        45 features in original data used to generate 45 features in processed
data.
        Train Data (Processed) Memory Usage: 9.03 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.51s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
```

```
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
AutoGluon will fit 2 stack levels (L1 to L2) …
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 39.65s of the
59.49s of remaining time.
        -32.5116         = Validation score   (-mean_absolute_error)
        0.03s    = Training   runtime
        0.33s    = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 39.24s of the
59.08s of remaining time.
        -32.5789         = Validation score   (-mean_absolute_error)
        0.03s    = Training   runtime
        0.33s    = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 38.84s of the
58.67s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -18.2707         = Validation score   (-mean_absolute_error)
        33.02s   = Training   runtime
        17.92s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 1.48s of the 21.32s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -20.6762         = Validation score   (-mean_absolute_error)
```

```
        1.8s     = Training   runtime
        0.13s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 59.49s of the
18.16s of remaining time.
        -18.2286         = Validation score   (-mean_absolute_error)
        0.34s    = Training   runtime
        0.0s     = Validation runtime
Fitting 9 L2 models …
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 17.81s of the
17.79s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -18.8409         = Validation score   (-mean_absolute_error)
        3.46s    = Training   runtime
        0.18s    = Validation runtime
Fitting model: LightGBM_BAG_L2 … Training model for up to 13.04s of the 13.03s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -18.6105         = Validation score   (-mean_absolute_error)
        2.05s    = Training   runtime
        0.07s    = Validation runtime
Fitting model: RandomForestMSE_BAG_L2 … Training model for up to 9.77s of the
9.76s of remaining time.
        -18.2066         = Validation score   (-mean_absolute_error)
        8.42s    = Training   runtime
        0.88s    = Validation runtime
Fitting model: CatBoost_BAG_L2 … Training model for up to 0.12s of the 0.11s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        Time limit exceeded… Skipping CatBoost_BAG_L2.
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L3 … Training model for up to 59.49s of the
-1.87s of remaining time.
2023-10-06 12:17:43,755 ERROR worker.py:399 -- Unhandled error (suppress with
'RAY_IGNORE_UNHANDLED_ERRORS=1'): The worker died unexpectedly while executing
this task. Check python-core-worker-*.log files for more information.
2023-10-06 12:17:43,758 ERROR worker.py:399 -- Unhandled error (suppress with
'RAY_IGNORE_UNHANDLED_ERRORS=1'): The worker died unexpectedly while executing
this task. Check python-core-worker-*.log files for more information.
2023-10-06 12:17:43,760 ERROR worker.py:399 -- Unhandled error (suppress with
'RAY_IGNORE_UNHANDLED_ERRORS=1'): The worker died unexpectedly while executing
this task. Check python-core-worker-*.log files for more information.
2023-10-06 12:17:43,762 ERROR worker.py:399 -- Unhandled error (suppress with
'RAY_IGNORE_UNHANDLED_ERRORS=1'): The worker died unexpectedly while executing
this task. Check python-core-worker-*.log files for more information.
```

```
2023-10-06 12:17:43,764 ERROR worker.py:399 -- Unhandled error (suppress with
'RAY_IGNORE_UNHANDLED_ERRORS=1'): The worker died unexpectedly while executing
this task. Check python-core-worker-*.log files for more information.
2023-10-06 12:17:43,767 ERROR worker.py:399 -- Unhandled error (suppress with
'RAY_IGNORE_UNHANDLED_ERRORS=1'): The worker died unexpectedly while executing
this task. Check python-core-worker-*.log files for more information.
2023-10-06 12:17:43,769 ERROR worker.py:399 -- Unhandled error (suppress with
'RAY_IGNORE_UNHANDLED_ERRORS=1'): The worker died unexpectedly while executing
this task. Check python-core-worker-*.log files for more information.
        -18.1341         = Validation score   (-mean_absolute_error)
        0.27s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 62.18s … Best model:
"WeightedEnsemble_L3"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_77_C/")
```

2 Submit

[9]:
```python
import pandas as pd
import matplotlib.pyplot as plt

train_data_with_dates = TabularDataset('X_train_raw.csv')
train_data_with_dates["ds"] = pd.to_datetime(train_data_with_dates["ds"])

test_data = TabularDataset('X_test_raw.csv')
test_data["ds"] = pd.to_datetime(test_data["ds"])
#test_data
```

```
Loaded data from: X_train_raw.csv | Columns = 49 / 49 | Rows = 93024 -> 93024
Loaded data from: X_test_raw.csv | Columns = 48 / 48 | Rows = 4608 -> 4608
```

[10]:
```python
test_ids = TabularDataset('test.csv')
test_ids["time"] = pd.to_datetime(test_ids["time"])
# merge test_data with test_ids
test_data_merged = pd.merge(test_data, test_ids, how="inner", right_on=["time",␣
  ↪"location"], left_on=["ds", "location"])

#test_data_merged
```

```
Loaded data from: test.csv | Columns = 4 / 4 | Rows = 2160 -> 2160
```

[11]:
```python
# predict, grouped by location
predictions = []
location_map = {
    "A": 0,
    "B": 1,
    "C": 2
```

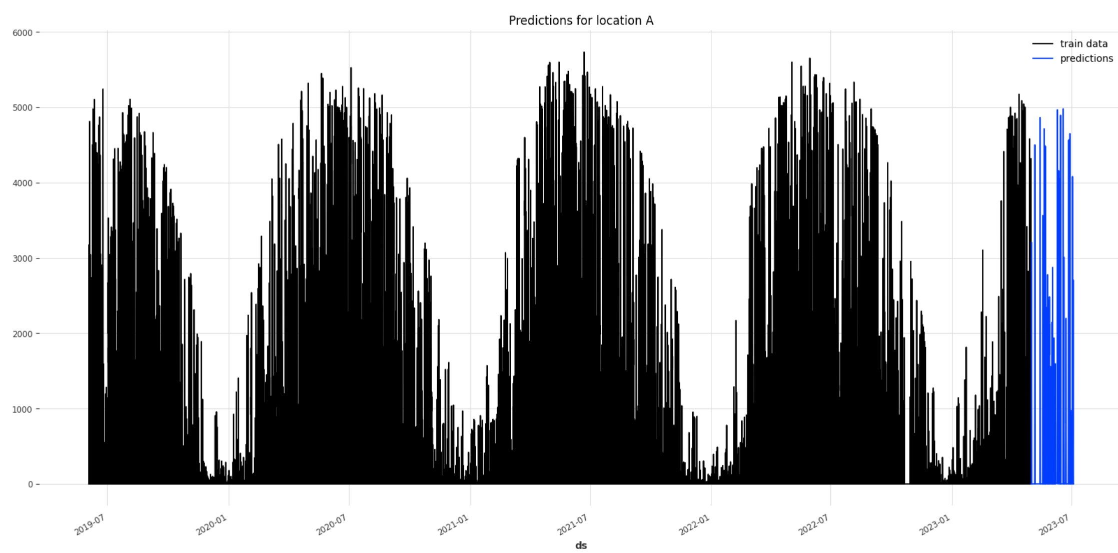
```
}
for loc, group in test_data.groupby('location'):
    i = location_map[loc]
    subset = test_data_merged[test_data_merged["location"] == loc].
 ↪reset_index(drop=True)
    #print(subset)
    pred = predictors[i].predict(subset)
    subset["prediction"] = pred
    predictions.append(subset)
```

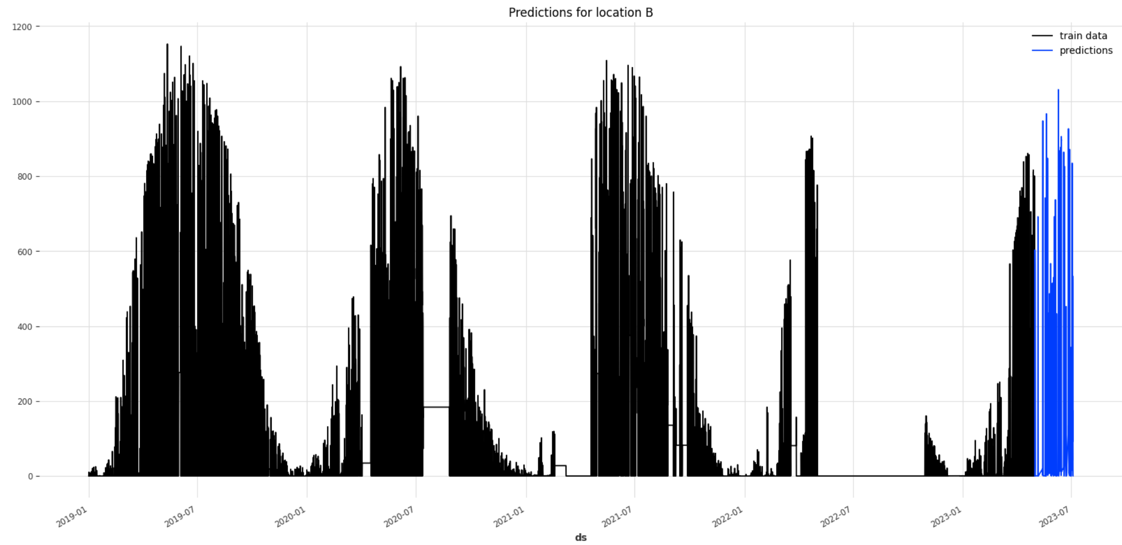
[12]:

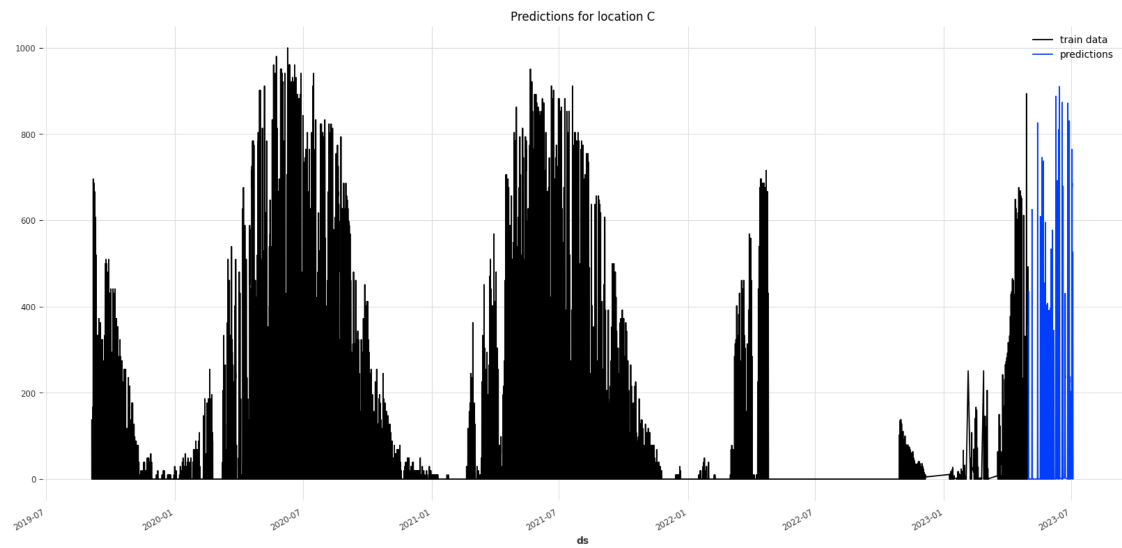
```
# plot predictions for location A, in addition to train data for A
for loc, idx in location_map.items():
    fig, ax = plt.subplots(figsize=(20, 10))
    # plot train data
    train_data_with_dates[train_data_with_dates["location"]==loc].plot(x='ds',␣
 ↪y='y', ax=ax, label="train data")

    # plot predictions
    predictions[idx].plot(x='ds', y='prediction', ax=ax, label="predictions")

    # title
    ax.set_title(f"Predictions for location {loc}")
```







[13]:
```
# concatenate predictions
submissions_df = pd.concat(predictions)
submissions_df = submissions_df[["id", "prediction"]]
submissions_df
```

[13]:

	id	prediction
0	0	1.280884
1	1	1.315760
2	2	1.439306
3	3	51.757767

```
4        4  255.222244
..     …          …
715  2155   94.525604
716  2156   85.884506
717  2157   32.355381
718  2158    5.549774
719  2159    1.691082

[2160 rows x 2 columns]
```

[14]:

```
# Save the submission DataFrame to submissions folder, create new name based on
↪last submission, format is submission_<last_submission_number + 1>.csv

# Save the submission
print(f"Saving submission to submissions/{new_filename}.csv")
submissions_df.to_csv(os.path.join('submissions', f"{new_filename}.csv"),
↪index=False)
```

```
Saving submission to submissions/submission_77.csv
```